Stereo Matching Technique using Belief Propagation

Annual Progress Seminar Report-II

Ph.D.

(Electronics Engineering)

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(Signature)

Abstract

The perception of depth is important criteria while visualizing 3D image.The disparity is difference in image location of same 3D point for 3D image ,when projected under different cameras.The stereo image is captured by two cameras at two different view point of same scene or object.
While finding disparity for stereo image two problems occurs,first problem is camera parameters and second one is finding corresponding point in right image for each point in left image which known as **stereo vision problem , stereo matching or stereo correspondence.**
The stereo matching problems can formulate in terms of Markov Random Field as minimum energy function, to find energy minimization function is NP-hard. This means a general solution to this problem will take an unthinkably long time to reach a solution. Belief propagation algorithm is an approach which find the approximate solution for minimum energy functions used for stereo matching.
keywords Stereo Image,Markov Random Field,Belief propagation

Contents

Chapter 1

Introduction

A person lives in a three-dimensional,spatial, environment ,without a feeling for space, cannot move within it.Our perception of space is created almost exclusively by our eyes. There are many ways to orient oneself in space, e.g., by perspective, gradation of color, contrast and movement.
The 3D experience comes from the left and right eye seeing slight different views .This effect is known as binocular vision.In binocular vision where separate images from two eyes are successively combined into one 3D image in the brain.
The perception of depth is important criteria while visualizing 3D image.The disparity is difference in image location of same 3D point for 3D image ,when projected under different cameras.
The method of finding depth from disparity is triagulation.

The stereo image is captured by two cameras at two different view point of same scene or object. While finding disparity for stereo image two problems occurs,first problem is camera parameters and second one is finding corresponding point in right image for each point in left image which known as stereo vision problem , stereo matching or stereo correspondence.
The camera parameters problem can be eliminated by using epipolar geometry,but stereo vision problem , stereo matching or stereo correspondence is challenging one. The stereo matching problem is reduced to a one dimensional search along horizontal lines instead of a two dimensional search by rectification
The stereo matching between two images is done by computing disparity of all the points on the object.The process involves identifying the corresponding points and finding the shift.
However, in practice if stereo images are available and there is no algorithm that finds the corresponding point or points showing corresponding objects. This is mainly because there is no procedure to identify the group of pixel from the same object.
The central problem of local or window based stereo matching methods is to determine the optimal size, shape and weight distribution of aggregation support for each pixel. However these techniques had limited success.
The stereo matching problems can formulate in terms of Markov Random Field as minimum energy function, to find energy minimization function is NP-hard. This means a general solution to this problem will take an unthinkably long time to reach a solution. Belief propagation algorithm is an approach which find the approximate solution for minimum energy functions used for stereo matching. The belief propagation is global algorithm performed over the whole images.In spite of having advantages of global algo-

rithm, there have been few real time stereo matching implementations due to their high complexity.
The Current research is directed towards optimizing the belief propagation algorithm.

This report is organized as follows:

The Introduction is discussed in chapter 1. Chapter 2 discusses Introduction to stereo matching chapter 3 discusses literature survey to find gap analysis. chapter 4 focuses on Research Methodology chapter 5 deals with MRF Implementation and Chapter 6 presents the conclusion and future work.

Chapter 2

Introduction to Stereo matching

A person lives in a three-dimensional,spatial, environment ,without a feeling for space, cannot move within it.Our perception of space is created almost exclusively by our eyes. There are many ways to orient oneself in space, e.g., by perspective, gradation of color, contrast and movement.
The 3D experience comes from the left and right eye seeing slight different views .This effect is known as binocular vision.The binocular vision shown in diagram 2.1

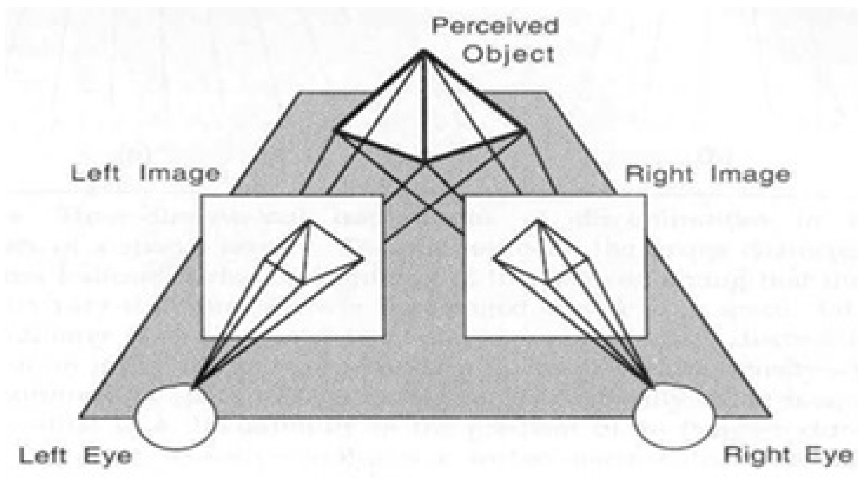

Figure 2.1: Principle of Binocular vision[7].

Binocular vision determines the position of a point in space by finding the intersection of the two lines passing through the center of projection and the projection of the point in each image.In binocular vision where separate images from two eyes are successively combined into one 3D image in the brain.
The above figure explains about appearance of objects in depth as perceived by normal binocular vision.
The perception of depth occur from disparity of a given 3D point in right and left retinal images. The method of finding depth from disparity is known as triangulation,which is shown in diagram 2.2. The 3D location of any visible object point in space is restricted to the straight line that passes through the center of projection and the projection of the object point. The formation of 3D image shown in diagram 2.3.

The disparity is difference in image location of the same 3D point for 3D image,when

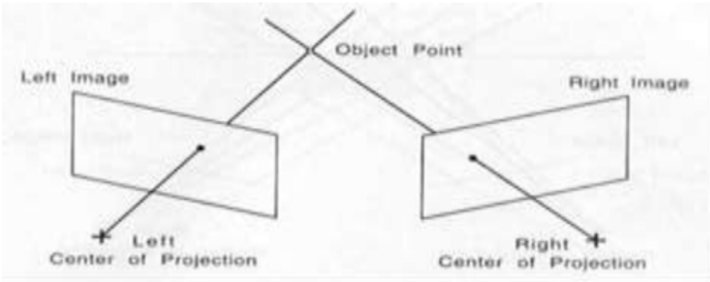

Figure 2.2: Principle of stereovision[7].

projected under two or more different cameras.
The stereo image is captured by two cameras at two different view point of same scene or object. Two problems arises when finding disparity for stereo image.They are

1. Use of prior knowledge or camera calibration

2. Finding corresponding point in right image for each point in left image which known as stereo vision problem , stereo matching or stereo correspondence.

The camera calibration may not required while using projectile approach for two images.The projectile approach is known as epipolar geometry which uses properties of rays rather than intrinsic parameters of camera.
The epipolar lines are the projection of the pencil of planes passing through the centers of the two or more images. The concept of epipolar lines shown in figure 2.4. Even for two images (or images with collinear camera centers) can find epipolar lines.

The image rectification is to make the epipolar lines of two camera images horizontally aligned. This may be accomplished by using linear transformations that rotate, translate and skew the camera images.
The principle of image rectification is shown in figure 2.5. The original camera image planes are drawn with solid borders and the rectified image planes are drawn with dashed borders. Epipolar lines are also drawn from the projected points p and p'to epipoles e and e'
After image rectification has been carried out, the epipolar lines of two projected points are parallel and horizontally aligned along the new image planes.
The stereo matching problem is therefore reduced to a one dimensional search along horizontal lines instead of a two dimensional search.
Camera images before rectification,pixel matching is a 2D search problem whereas Camera images after rectification,pixel matching can be done through a one dimensional line search. Camera images before rectification, pixel matching is a 2D search problem while

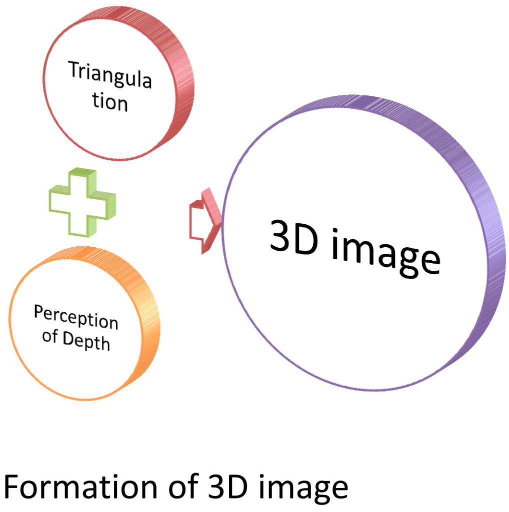

Figure 2.3: 3D Image formation

Camera images after rectification ,pixel matching can be done through a one dimensional line search,which is shown in figure 2.6.

2.1 Disparity and Disparity map

In stereo matching, the target is to find matching pixels of two given input images and the result from finding matching pixels is normally saved as a disparity map. The term disparity can be looked upon as horizontal distance between two matching pixels and the disparity map defines a value of this horizontal pixel distance for each image pixel coordinate. Hence, it may be seen as a function of d(x, y) image pixel coordinates
In practice, depth maps are stored as gray scale images that show distance instead of texture. This means that an object located close to the camera turns out bright while a faraway located object looks darker (or vice versa).
The relation between intensity and distance has to be specified somehow (e.g. by defining the nearest and farthest distance values of the intensity range 0-255) The diagram 2.7 explains about depth map for stereo image.

The solution to stereo matching problem is described as a flow chart in diagram 2.8.

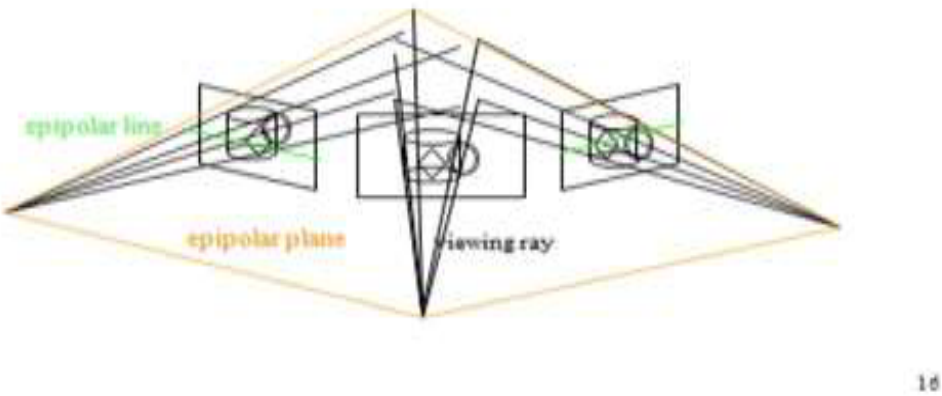

Figure 2.4: Projectile concept(Epipolar geometry)[7]

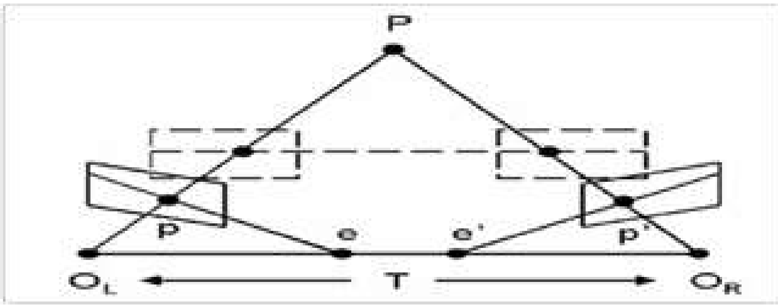

Figure 2.5: Principle of Rectification[7]

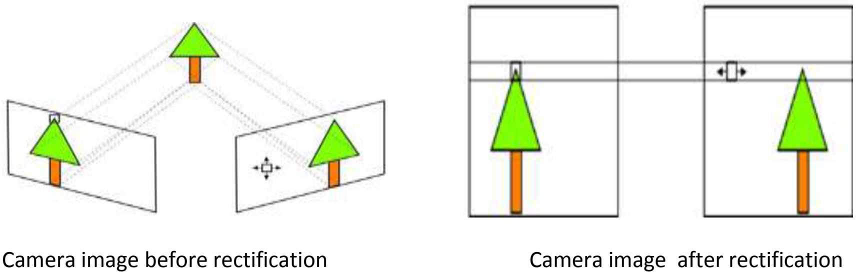

Figure 2.6: Camera images before and after rectification[7]

Figure 2.7: 2D camera image and Depth map belonging to the image[7]

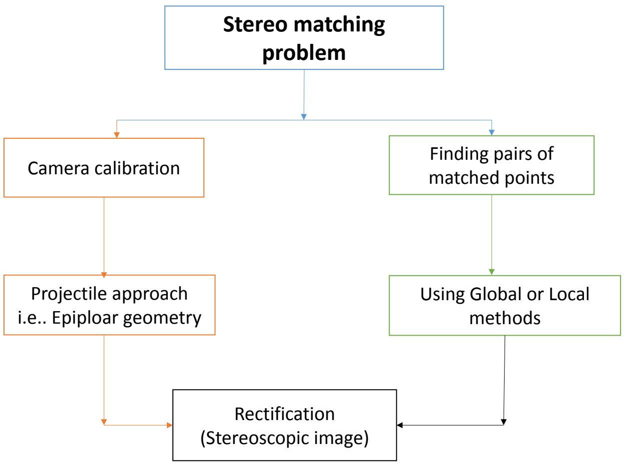

Figure 2.8: Flow chart for stereo matching

Chapter 3

Literature Survey

The major contribution in the field of stereo matching using Random Markov field and inference algorithm like Belief Propagation
[2003] Comparison of Graph cuts with Belief Propagation for stereo, Using Identical MRF Parameters:[1]
The disparity image can be achieved by modelling Markov Random Field and by using optimization algorithm such as Graph cut and Belief Propagation. These two algorithm allow fast and approximate solution to MRF which are powerful tools for modelling vision problems.so one system improvement over the other be attributed to its choice of an inference algorithm.
The comparison between Graph cut algorithm with max product Belief Propagation algorithm shows that the solution for energy by Graph cut and Belief Propagation algorithm nearly equal although graph cut consistently returns smaller energy. The solutions produced by Graph cut are smoother while accelerated Belief Propagation algorithm was faster.
Given this situation Improving formulation of MRF rather than improving solution (optimization algorithm) for MRF. The comparisons between inference algorithm such as Graph cut and Belief Propagation depends on the functions of MRF formulation.
The future research can be different functions such as truncated linear or quadratic used for MRF optimizing with any one of the inference algorithm[1]
[2004] Efficient Belief Propagation for Early Vision:[2]

The early vision problems such as stereo, optical flow and image restoration can be solved by MRF model by using inference algorithm based on Graph cut and Belief propagation In this paper new algorithm techniques improve the running time of the algorithm. The inference algorithm used is max product belief propagation.
The three techniques substantially reduces time required to compute the message updates.

1. In low level vision problems the label or hidden node is generally based on some difference between two labels rather than on particular pair of labels, this is known as distance transform technique. This technique reduces message computing time.

2. In new message update scheme, here nodes are split into two Messages are updated alternately ,so half of the messages only updated at each iteration.so memory required to store messages are reduced.

3. The third technique uses hierarchical structure to reduce the number of message passing iterations to small constant rather depends on size of the image grid.

[2007] Low Memory Cost Block Based Belief Propagation for Stereo Correspondence[3]
The global approaches can handle the texture less and occluded regions well by formulating disparity inference as an energy minimization problem. The energy functions usually has smoothness constraint which represents a certain relationship between neighboring pixel pair. This smoothness constraint enforces penalty on the energy function, if the labels (disparity or segments)of neighboring pixel are inconsistent.
The 2D optimization algorithm such as graph cut and Belief Propagation have been applies successfully to optimize energy functions. The BP algorithms construct 2-D graph structures with nodes represent all pixels in the disparity image to find the disparity map with energy closer to the global minima. However, the vast number of nodes in 2-D graph result in extremely high computation complexity too difficulty in real time applications.
The proposed Block based Belief Propagation algorithm directly partitions image into separated independent blocks.so memory size reduces significantly due to block based computation. With block based design, the criterion of convergence becomes important for each block.
In general, the criterion of convergence in belief propagation is defined with the saturation of energy functions. The specific threshold is set to terminate the belief propagation process. However it is difficult to find a global threshold for each block. In proposed algorithm find the convergence according to the equivalence of all disparities for each node in a block over successive iterations.
[2009] Hardware-Efficient Belief Propagation[4]
Loopy belief propagation is an effective solution for assigning labels to the nodes of a graphical model such as Markov Random Field, but requires high memory, bandwidth and computational costs. In this paper two techniques are proposed

1. Tile based Belief propagation ,when message is updated data of nodes which are far away are not required, so MRF is divided into multiple regions known as tile and iterations are done on those regions. So memory required to store messages are reduced.

2. Fast message construction:The cost functions serve for measuring the compatibility between the labels and the observations or prior knowledge. For example in stereo matching that the disparity values vary smoothly between neighboring pixels. However this assumption is valid only when corresponding pixels belong to the same object. otherwise the difference between their disparity values can be arbitrarily large resulting high cost value. In fast message construction using robust function is used as smmothness cost.

Table 3.1: Optimization methods used for finding the disparity from various research papers

The summary of literature survey is mentioned in table

Research paper	Optimization Method	Scope for Research
Comparison of Graph cuts with Belief Propagation for stereo, Using Identical MRF Parameters [2003]	Comparative study of Graph cut and Belief Propagation on same MRF Model	Further study of Improving formulation of MRF rather than improving solution for MRF
Efficient Belief Propagation for Early Vision [2004]	Three methods are used 1. Distance transform technique(difference between two labels) 2. New message update scheme 3. Hierarchical structure	Further study can be: These optimization method can be applicable to a broad range of more sophisticated cost functions.
Low Memory Cost Block Based Belief Propagation for Stereo Correspondence [2007]	2D BP Graph is divided into blocks. Optimize each block separately.	The information exchange between Neighboring finished processing block and unfinished processing block can be further investigated
Hardware-Efficient Belief Propagation [2009]	Efficiency of BP is improved by new message scheme known as Tile based BP and Fast message construction	The performance Tile based message passing scheme can be studied for different conditions like different smoothness cost functions

Chapter 4

Research Methodology

The stereo matching between two images is done by computing disparity of all the points on the object. Theoretically, the process involves identifying the corresponding points and finding the shift.
However, in practice two images are available and there is no 'algorithm' that finds the corresponding point or points showing corresponding objects. This is mainly because there is no procedure to identify the group of pixel from the same object.
The central problem of local are window based stereo matching methods is to determine the optimal size, shape and weight distribution of aggregation support for each pixel. However these techniques had limited success.
Belief propagation algorithm is one of the possible inference algorithm can be applied for calculating stereo disparities. the Loopy Belief Propagation (LBP) is an iterative process that works well. It is also computationally simple.

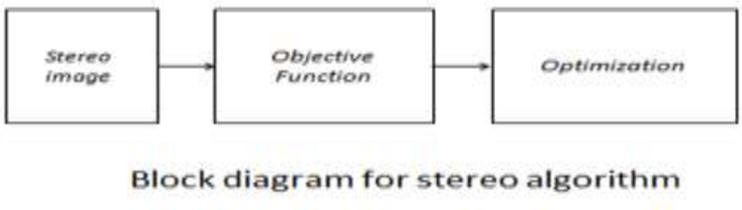

Figure 4.1: Block diagram for stereo algorithm

The stereo images are known as stereo pairs have been rectified such that each pixel row on the left image perfectly corresponds to the right.
The objective function is Markov Random Field (MRF)formulation .MRF is a powerful tool and effective probabilistic model used for stereo matching technique. MRF are undirected graphical models that can encode spatial dependencies. The stereo problem can be modelled using an MRF.

4.1 MRF formation for stereo image

Given rectified stereo pair of images, the goal is to find the disparity of each pixel in the reference image.
For each possible disparity value, there is cost associated with the matching pixel to the corresponding pixel in the other stereo image at that disparity value. This cost is known as datacost which is based on the intensity differences between the two pixels. The Sum of Absolute Difference(ABS) or Sum Of Square Difference(SSD) functions are used as datacost compatibility.
A MRF approach uses second compatibility function which expresses compatibility between neighboring variables. This is known as a pair-wise Markov Random Field. A pair-wise Markov Random Field are used for stereo problems because each variable is able to influence every other variable in the field through pair -wise connections. A pair-wise compatibility function is known as smoothnesscost function.
The MRF is defined in terms of energy function rather than compatibility functions.The energy function ie.datacost which corresponds to the matching cost computation and smoothnesscost is computed using Birchfield-Tomasi matching cost.For numerical reasons these compatibility cost (c)is converted into $\exp^{-c}$.

4.2 Belief Propagation

The belief propagation algorithm was proposed by Pearl in 1988 for finding exact marginals on graphs that contain no loops, It can be applied to the graphs which contain loops known as loopy belief propagation. The loopy belief propagation (LBP) algorithm is approximate inference algorithm which passes the messages around network until stable belief state is reached.
LBP is a iterative message passing algorithm. A node passes a message to an adjacent node only when it has received all incoming messages, excluding the message from the destination node to itself. Below shows an example of a message being passed from x_1 to x_2. Node x_1 waits for messages from nodes A,B,C,D before sending its message to x_2 . As a reminder, it does not send the message from $x_2 \longrightarrow x_1$ back to x_2 .

There are two steps in LBP iterative inference algorithm :

1. Message update :There are three methods to message update, any one is used for message update
   (a) Sum-Product : Sum of probabilities calculated, for each label normalized and maximum is taken
   (b) Max- Product: Label of Max probability is taken.
   (c) Min-Sum: Here the cost is considered and min cost is taken
2. Calculating Belief

The Max-product algorithm is explained with help of diagram shown below;

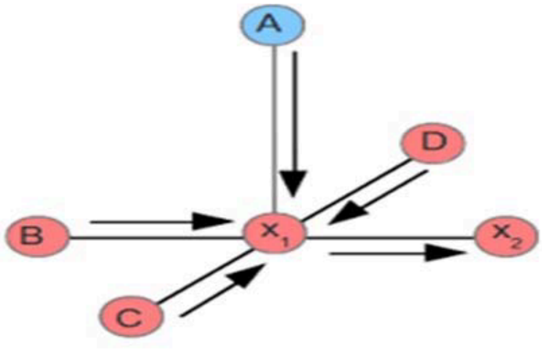

Figure 4.2: Message passing in BP[6].

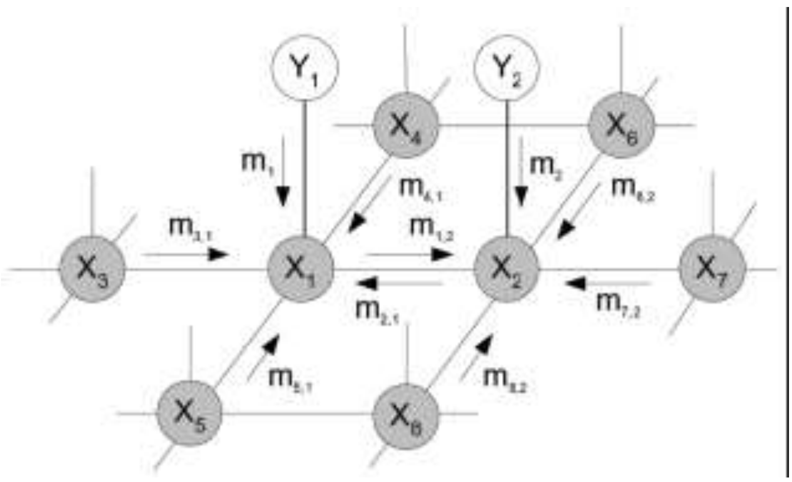

Figure 4.3: Message passing in max product LBP[8].

In Message passing in max product LBP diagram white nodes are observable variable which is is the right image intensity values.
Gray nodes are hidden variable which is shift values or labels(initial disparity map) In max product algorithm,the new message sent from node x_2
For t iterations
Message update
$m_{1,2}^{new} \leftarrow max_{x1}\psi(x_1, x_2)m_1 m_{3,1} m_{4,1} m_{5,1}$
where as

$\psi(x_1, x_2)$ is compatibility matrix between node $x_1 x_2$

m_1 is local evidence from node y_1

$m_{3,1} m_{4,1} m_{5,1}$ are neighboring evidence from shift values or labels

The belief at node x_1 is computed as
$b_1 \leftarrow$ K$m_1 m_{2,1} m_{3,1} m_{4,1} m_{5,1}$

- K is Normalization constant
- The product of two messages is component wise product

The computational complexity of Max product LBP algorithm is $O(TNL^2)$
Where

T is number of iterations

N is number of pixels

Lis number of discrete states or label

Chapter 5

MRF Implementation

The formation of MRF can be expressed as energy functions.The energy functions are implemented by considering following points:

1. Stereo as a energy minimization uses two functions like data cost or match cost which find good match in the right image for each pixel.Another functions smoothness cost function ,if two pixels are adjacent,they move about same amount.

2. $$Matchcost = \sum_{x,y} |I_{x,y} - J_{x+label,y}| \tag{5.1}$$

   $I_{x,y}$ is Left Image

   $J_{x,y}$ is Right Image

   Label or Disparity=16

3. 4-connected neighborhood is considered for Smoothness cost

4. $$Smoothnesscost = \sum_{neighborsofp,q} f\{min(|d_p - d_q|), 2\} \tag{5.2}$$

   Truncated linear mode is used as Smoothness cost

   d_p is pixel intensity values from left image i.e.Reference image

   d_q is Summation of 4-connected neighbors from right image i.e.Disparity image

5. Energy function =Matchcost function + smoothnesscost function

6. The energy function by keeping label has 16,for teddy and tsukuba stereo image pair shown below:

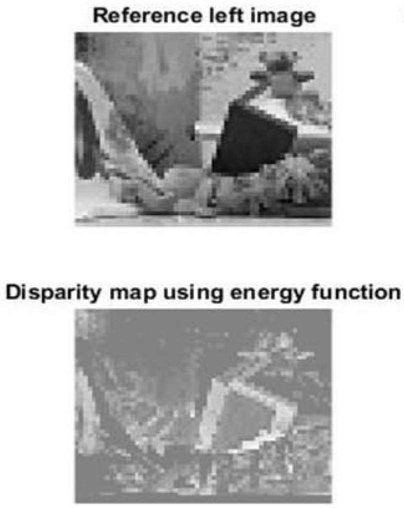

Figure 5.1: For tedy stereo pair and its disparity using MRF energy functions

Figure 5.2: For Tsukuba stereo pair and its disparity using MRF energy functions

Chapter 6

Conclusion

The terms and concepts related to Markov Random Field (MRF)formulation and Message updates in iterative inference belief propagation are studied.
Literature survey on major contribution in the field of stereo matching using Markov Random field and inference algorithm like Belief Propagation are studied to find gap analysis for further research.
Implemented Markov Random Field (MRF)formulation
Future Work is to improve the disparity map which is produced by Markov Random Field by using iterative inference Belief Propagation algorithm

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